Input-Output Analysis (Subject Editor: Sangwon Suh)

A Risk-Based Approach to Health Impact Assessment for Input-Output Analysis
Part 1: Methodology*

Yurika Nishioka, Jonathan I. Levy, Gregory A. Norris, Deborah H. Bennett and John D. Spengler**

Harvard School of Public Health, Department of Environmental Health, Landmark Center West-4, P.O. Box 15677, Boston, MA 02215, USA

** **Corresponding author** (ynishiok@hsph.harvard.edu)

DOI: http://dx.doi.org/10.1065/lca2004.10.186.1

Abstract

Goal, Scope and Background. Incorporation of exposure and risk concepts into life cycle impact assessment (LCIA) is often impaired by the number of sources and the complexity of site-specific impact assessment, especially when input-output (I-O) analysis is used to evaluate upstream processes. This makes it difficult to interpret LCIA outputs, especially in policy contexts. In this study, we develop an LCIA tool which takes into account the geographical variability in both emissions and exposure, and which can be applied to all economic sectors in I-O analysis. Our method relies on screening-level risk calculations and methods to estimate population exposure per unit of emissions from specific geographic locations.

Methods. We propose a simplified impact assessment approach using the concept of intake fraction, which is the fraction of a pollutant or its precursor emitted that is eventually inhaled or ingested by the population. Instead of running a complex site-specific exposure analysis, intake fractions allow for the accounting of the regional variability in exposure due to meteorological factors and population density without much computational burden. We calculate sector-specific intake fractions using previously-derived regression models and apply these values to the supply chain emissions to screen for the sectors whose emissions largely contribute to the total exposures. Thus, the analytical steps are simplified by relying on these screening-level risk calculations. We estimate population exposure per unit emissions from specific geographic locations only for the facilities and pollutants that pass an initial screening analysis. We test our analytical approach with reference to the case of increasing insulation for new single-family homes in the US. We quantify the public health costs from increasing insulation manufacturing and compare them with the benefits from energy savings, focusing on mortality and morbidity associated with exposure to primary and secondary fine particles ($PM_{2.5}$) as well as cancer risk associated with exposure to toxic air pollutants. We estimate health impacts using concentration-response functions from the published literature and compare the costs and benefits of the program by assigning monetary values to the health risks. In the second part of this paper, we present the results of our case study and consider the implications for incorporating exposure and risk concepts into I-O LCA.

Conclusions. We have presented a methodology to incorporate regional variability in emissions and exposure into input-output LCA, using reduced-form information about the relationship between emissions and population exposure, along with standard input-output analysis and risk assessment methods. The location-weighted intake fractions can overcome the difficulty in incorporation of regional exposure in LCIA.

Keywords: Air pollution; cost-benefit analysis; fiberglass insulation; input-output analysis; intake fraction; life cycle impact assessment; public health; risk analysis

Introduction

In life cycle assessment (LCA), emission inventories of products and services are interpreted in terms of final impact categories during the impact analysis step. The impact analysis step is often a barrier to a complete LCA because of data limitations and the computational burden. A conventional approach for characterizing end-point impacts involves the characterization and normalization of pollutants, with the final score representing a weighted sum of various impacts. The conventional approach does not provide impact values per se (e.g. number of premature deaths), but only a scale of impacts relative to a somewhat arbitrary reference value, such as annual emissions of $PM_{2.5}$ at a national or global level. This approach may be used to screen the relative importance of potential impacts. However, when these conventional approaches do not take into account the influence of emissions on exposure, they fail to account for the regional and source-related variability of impacts.

Without an impact assessment step, a life cycle inventory analysis can only indicate how options affect the total mass quantities of each pollutant released over the life cycle. A spatially generic impact assessment approach leads decision makers to choose products and services that simply reduce the quantity of potentially harmful pollutants, regardless of location. However, such a simplified approach can be misleading because emissions in densely populated areas would lead to more health impacts than emissions in less populated areas, and because atmospheric conditions would influence pollutant fate and transport differently in different areas. To account for exposure, an extensive site-specific risk assessment would be useful, but is often not practical because of the number of sources. In particular, for input-output (I-O) analysis, the number of plants involved in a supply chain increases exponentially as more tiers of upstream processes are included. While total supply chain emissions can be calculated using an I-O model with many fewer system boundary limitations than the process-based approach, site-specific impact assessment for every emission site with traditional fate and transport modeling has never been performed, for this reason. Therefore, a simplified approach is needed to incorporate exposure and risk concepts into LCA, especially for input-output LCA.

In this paper, we propose a sector-specific impact analysis using intake fractions (defined later in the text) as a new

* Part 2: Case Study of Insulation
(DOI: http://dx.doi.org/10.1065/lca2004.10.186.2)

tool to estimate risks from I-O emission inventories. Our methodological goal is to develop a life cycle impact assessment (LCIA) tool which takes into account the geographical variability in both emissions and exposure, and which can be applied to all economic sectors in I-O analysis as specified by the US Bureau of Economic Analysis (BEA). We also aim to develop a two-step approach in which site-specific fate and transport modeling is only conducted for facilities and pollutants that pass an initial screening analysis.

We test our approach by considering increased insulation for new single-family homes in the US. The goal of our case study, which is presented in full in the second part of this paper, is to quantify the public health costs and benefits of increasing insulation from current practice to the levels recommended by the 2000 International Energy Conservation Codes (IECC 2000). In an earlier analysis [1], Nishioka et al. developed a risk-based model to quantify health impacts associated with savings in heating and cooling energy, focused only on the end-use emission reductions. This study found that increased insulation in all new, single-family homes built each year would save 5×10^{15} joules, with reduced emissions of approximately 20 metric tons of $PM_{2.5}$, 400 metric tons of NO_x, and 700 metric tons of SO_2, which in turn would lead to 1.1 fewer fatalities, 30 fewer asthma attacks and 500 fewer restricted activity days (RAD) per year. The geographical distribution of health benefits was different from the distribution of energy savings due to differences in energy sources, population densities, and meteorology.

One past LCA study of demand-side management tried to address the issue of regional variability in emissions and exposure for homes built in Germany. Hohmeyer and Brauer reported the external costs of upstream processing of insulation materials, assuming that all houses built between 1959 and 1968 were being renovated and that new insulation measures (German Thermal Insulation Ordinance 1995) were applied [2]. This study calculated external costs of human health impacts from particulate matter and aerosols, and agricultural damage from sulfur dioxide, by localizing two-thirds of both direct and indirect emissions based on process-based LCA and site-specific impact assessment. One of the key findings was that ignoring the intermediate processes that are beyond the scope of the process-based LCA (i.e. goods that are necessary for the production of the goods directly consumed by the final processing sector) underestimates total emissions by 30 to 50% for thermal insulation.

In our current analysis, we focus on the supply chain processes for increased insulation and decreased fuel consumption. We first use our model to estimate impacts associated with the supply chain emissions and identify the major contributors to total health impacts. In a second stage of the analysis, we refine impact estimates by running air dispersion models for seven of the top emission sites that together account for 50% of the total primary $PM_{2.5}$ emissions. The health outcomes of interest are mortality and morbidity associated with exposure to fine particles as well as cancer risk associated with exposure to toxic air pollutants. For cancer cases, we focus on 143 Toxics Release Inventory (TRI) pollutants for which exposure and toxicity information are available. We finally compare the costs and benefits of the program by assigning monetary values to the health risks. Our case study framework is similar to that of the German study, but the analytical framework is somewhat different since our approach allows for accounting of the full range of supply chain emissions.

In our analysis, we demonstrate that a meaningful comparison of the benefits and costs of increased insulation requires an integration of LCA and risk assessment. Our approach is not site-specific at the establishment level, *per se,* but it allows an incorporation of site-information for the exposure and risk estimates to the extent it is pragmatic, without involving expensive data collection efforts, while expanding the system definition within the I-O framework.

1 Case Study Framework and Background

1.1 Scope of analysis

From an LCA perspective, it is important to look at not only the end-use energy savings of increased insulation, but also the upstream manufacturing stages of insulation and fuel sources. From a public health perspective, the important question is whether the additional health effects from the manufacturing stage would be recouped, within the lifetime of the house, by the health effects avoided by the end-use energy savings. The schematic diagram of our scenario is shown in **Fig. 1**. Although it is critical to capture the full range of impacts when LCA is used for policy prescriptions, it should be noted that, in our case study, we focus only on impacts associated with the supply chain of insulation and fuel sources as well as end-use energy savings. Installation, use and disposal of fiberglass may impose additional external effects, but are not included in our analysis. The orthodox approach would be to expand the Input-Output model to include the column for 'new housing construction' to account for the components that would be affected by increased insulation (e.g. installation), but we chose a more practical approach by using the existing economic tables. Furthermore, while there are clearly impact categories beyond human health that are crucial to LCA and they would be influenced by increased insulation, we focus on the health endpoint to illustrate linkages with risk assessment and issues related to spatial variability.

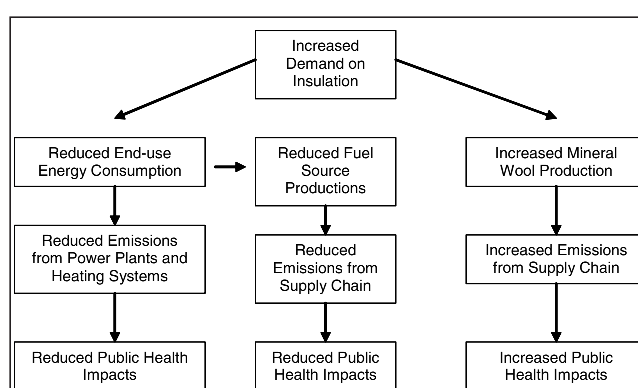

Fig. 1: Schematic depiction of benefit-cost case study of increased residential insulation

1.2 Energy model

In a previous analysis [1], Nishioka et al. developed an energy model for calculating total end-use energy savings in each state as a result of increased insulation. REM/Design (Architectural Energy Corporation, Boulder, CO) was used to calculate heating and cooling energy consumption for prototype homes representing various combinations of housing characteristics such as insulation level, floor area, heating system, foundation type, and number of stories. The outputs from REM/Design were used to develop regression models based on ASHRAE (American Society of Heating, Refrigerating and Air-Conditioning Engineers) standard heat loss equations. Nishioka et al. used the regression approach to calculate energy savings associated with incremental R-values (the thermal resistance in ft² °Fh/Btu) for each state for the given distribution of housing characteristics. The total estimated energy saving was about 5×10^{15} joules per year per single-year cohort of new homes, with the highest savings in the South and the Midwest regions [1].

1.3 Risk-based model

Heating and cooling energy savings lead to lower emissions from power plants and household heating systems. Emission reductions in turn lead to lower exposure to pollution for the population living in the regions where pollutants are dispersed. The regional variability in fuel utilization, population density, and meteorological conditions leads to a distribution of risks that is not directly proportional to energy savings. Therefore, a risk-based approach is needed for comprehensive health impact analysis for increased insulation.

Exposure may be most accurately estimated by air dispersion models. However, application of dispersion models to the number of sources in an I-O analysis is infeasible. To estimate population exposure in situations where dispersion modeling cannot be conducted, researchers have developed a concept known as an intake fraction. Intake fraction is defined as a dimensionless ratio between the amount of pollutant intake and the amount of a pollutant emitted [3,4]. In other words, it is the fraction of a pollutant or its precursor emitted that is eventually inhaled or ingested. Mathematically, intake fraction is defined as:

$$iF = \frac{\sum_i C_i \times BR \times N_i}{Q} \tag{1}$$

where C_i = incremental concentration of pollutant at area i (µg/m³); BR = breathing rate (20 m³/day on average); N_i = number of people at area i; Q = emission rate of pollutant or pollutant precursor (µg/day). Assuming a linear dose-response relationship throughout the range of ambient concentrations in the affected areas and the fact that the health effects are not dose-rate dependent, intake fraction can be directly translated into risk. Thus, intake fraction is a powerful tool because it can be derived from previous air dispersion models and used where site characteristic data are limited or the number of emission sites is large.

CALPUFF, a Lagrangian puff model with a non-steady-state modeling system, has been frequently used for estimating intake fractions of fine particles for power plants and mobile sources in the United States [5–7]. The model is suitable for modeling long-range transport of pollutants and formation of secondary pollutants such as nitrates and sulfates [8]. These features have made the model preferred over short-range models such as the Industrial Source Complex Model (ISCST3).

In a previous analysis [1], Nishioka et al. used mobile source intake fractions for emissions from household heating systems and power plant intake fractions for electricity-related emissions. Those intake fractions were linked with concentration-response functions to estimate health effects, relying on the past air pollution epidemiological literature to derive concentration-response functions for mortality and morbidity. For premature mortality, the American Cancer Society (ACS) cohort study was used for our central estimate [9]. For morbidity, the previous analysis used Whittmore and Korn (1980) for asthma attacks and Ostro and Rothschild (1989) for RAD [10–11].

2 Methods

The overall framework of our upstream analysis for insulation and fuel sources consists of the following steps:

- Determining the incremental economic outputs induced by the incremental final demand increase for fiberglass and related decrease for fuel sources (natural gas, oil, electricity) by complying with IECC 2000
- Estimating emissions from the incremental economic outputs and sector-specific emission factors
- Estimating exposure to the additional emissions of air pollutants considered to affect human health at current ambient levels
- Quantifying health impacts associated with the incremental exposure
- Monetizing the incremental health impacts and comparing the total societal costs with the total societal benefits

For the inventory analysis, we calculate the direct and upstream economic outputs of insulation and fuel sources, assuming average, proportional increases of industrial activities throughout the United States. This is a conventional LCA approach, where an average instead of marginal effect is attributed to a unit increase of demand. However, our analysis is refined in that regional variabilities of industrial activities and their emissions are taken into account in calculating intake fractions, while the conventional approach assumes that the exposure is uniform throughout the country, regardless of the location of emission sources and population. Thus, although the exact location affected by an incremental demand is not known in the inventory analysis, the regional information is incorporated in the exposure analysis.

For mortality and morbidity effects, as previously, we focus on $PM_{2.5}$ as well as NO_x and SO_2 as particulate matter precursors. For cancer risks, we focus on toxic air pollutants as listed in TRI [12]. Our assumption is that fine particles ($PM_{2.5}$) are likely to explain a significant fraction of the total health risks, with the evaluation of toxic air pollutants

needed in initial screening calculations. These assumptions are consistent with national analyses of the health effects of particles and hazardous air pollutants [13–14]. Other criteria pollutants such as CO and ozone could cause additional health impacts. However, past US EPA benefit-cost analyses [15] along with our emission profiles confirm that the magnitude of impacts from the excluded pollutants is probably small compared to the magnitude of impacts from particulate matter.

Intake fractions are used to account for the regional variability in exposure due to meteorological factors and population. Additional analysis on stack height effects is incorporated where a detailed analysis is necessary.

2.1 Total output estimation

To calculate the incremental economic outputs induced by increased insulation and reduced fuel consumption, we use OpenLC, Analytica-based software for input-output modeling (available from Greg Norris upon request). OpenLC utilizes BEA's 'make' and 'use' matrices, together with an industry-technology assumption, to create an industry-by-industry direct requirement matrix (A Matrix) to calculate the total economic outputs induced by a demand [16]. The 'make' matrix specifies the value (in producers' prices) of output of each commodity from each industry. The 'use' matrix specifies the value (in producers' prices) of each commodity input to each industry. The columns of the direct requirement matrix report the dollar values, in producers' price, of the row industries' output that is used by the column industries to produce one dollar of output. These matrices are used to calculate both tier-wise and total economic output (direct and upstream) from the economy, given the incremental output from the industries of interest, namely the mineral wool and fuel production sectors.

To convert the mass of fiberglass into a dollar value, we estimated the unit value (dollar/ton) based on the total value of shipment by the industry [17] and the estimated mass of fiberglass production [18]. However, the value of shipment includes the economic output of both fiberglass and non-fiberglass manufacturers. Since information such as price of fiberglass insulation at the plant-level is proprietary, to revise the unit value of fiberglass/mineral wool insulation, we gathered a list of fiberglass manufacturers as well as the number of employees reported in County Business Patterns data. We assumed that the number of employees is a reasonable proxy for the economic output at each plant. Since the number of employees is often given as a range, we constructed an uncertainty model (assuming uniform distributions within all reported ranges) that provides the upper and lower bounds of the economic outputs for fiberglass/mineral wool manufacturers.

For the incremental dollar value of the fuel savings, we first calculated the demand reduction in consumer's price based on the total energy savings from our previous analysis and the unit price of fuel sources as reported by EIA [19–21]. We then applied the price content of fuel sources to derive the economic value at the producer's price [21–23].

2.2 Emission estimation

Given the estimated changes in total industrial outputs, we quantify the incremental emissions of $PM_{2.5}$, NO_x, SO_2 and TRI pollutants. The pollution intensity matrix T is used together with the total output matrix X to calculate the total emissions associated with the incremental demand for fiberglass/mineral wool and fuel sources. We derive the pollutant intensity matrix based on EPA's AIRS data for $PM_{2.5}$, NO_x, and SO_2 and EPA's TRI data for the toxic air pollutants. The pollution matrix is defined as the pollutant-by-industry matrix whose columns report pollutant releases per million dollars of output from the column's industry. Thus, the total pollutant emissions are calculated as:

$$P = TX = T(y + Ay + A^2y + A^3y + A^4y \ldots + A^ny) \qquad (2)$$

where T= pollution intensity matrix; X = incremental total output matrix; y = incremental final demand; A^ny = the nth tier output.

2.3 Exposure estimation

For sources whose intake fractions have not been previously evaluated, regression models for intake fractions can be applied [6]. With the regression approach, intake fractions are estimated with limited data such as simple source characteristics (e.g. stack height), meteorological parameters and population distributions. For example, intake fractions increase with population density, and stack height influences the intake fraction of primary but not secondary particles. This approach is especially powerful for an I/O-based impact analysis, which involves numerous emission sites.

In exposure analysis, it is important to determine the scope and resolution of receptors that can capture the distribution of exposure reasonably well. The travel distance of secondary fine particulate matter, including sulfates and nitrates, can be up to thousands of kilometers from the source [24]. Therefore, we determined that a state level analysis should give a reasonable estimate of intake fractions for secondary fine particles for any sources within the state. For primary $PM_{2.5}$, the taller the stack height, the lower the intake by population around the source. Since the stack height of power plants is among the highest across manufacturing sectors, their intake fractions represent the lower bound for all industries. On the other hand, mobile sources represent ground-level emissions, for which exposure to primary fine particles is more concentrated around the source, with a travel distance ranging up to tens or hundreds of kilometers. Therefore, their intake fractions can be considered the upper bound.

For industries whose stack height falls somewhere between those two extreme values (e.g. fiberglass manufacturers), intake fractions need to be extrapolated given regression models based on power plants and ground-level sources. Although the power plant regression model for primary $PM_{2.5}$ includes a term for stack height, the log-linear model structure poses difficulties for stack heights outside the range for power plants. The simple average value of the upper and

lower bounds is a reasonable first approximation of intake fractions for industries with lower stacks. However, this approach does not tell us whether the central estimate is likely to overestimate or underestimate the true intake fraction. Thus, a refined analysis is warranted for the manufacturing facilities whose primary $PM_{2.5}$ emissions contribute significantly to the final impacts. For our case study, primary $PM_{2.5}$ emissions were an important source of exposure and, therefore, we needed to come up with an approach to estimate intake fractions for the fiberglass/mineral wool manufacturers. Our approach is detailed in Section 2.5 (Refined Analysis).

2.4 First-level analysis

Our upstream exposure analysis for fine particles consists of two levels of resolution. For the first-level analysis, we apply the sector-specific emission-weighted intake fractions to the emission inventory from input-output analysis. In this stage, we assume that all industrial sources are hypothetically situated at the centroid of each state, and we do not directly account for stack height. Therefore, for all the state centroid locations, we calculate the upper and lower bounds and the central estimates of intake fractions using the past regression models [6] with the parameters listed in **Table 1**.

We calculate the lower bound of primary $PM_{2.5}$ intake fractions using the 95th percentile of stack height for the utility industry (227 m). The population data were obtained from the Center for International Earth Science Information Network (CIESIN) at Columbia University [25], which gives the population within a 2.5' x 2.5' grid across the world. The climate data were obtained from the National Climatic Data Center and US EPA. To estimate climate values at the state centroid locations, gridded climate data were first generated in Surfer® using our previously calculated values for Metropolitan Statistical Areas (MSAs) and power plant locations [1]. The inverse distance weighting interpolation method is used to estimate values for the state centroid locations.

We weight the regression-based intake fractions by emissions from each state to estimate the emission-weighted intake fractions. For this purpose, the plant-level emissions data obtained from EPA are aggregated by sector and state. Mathematically, this is written as:

$$iF_j = \sum_i iF_i \times P_{ij} \tag{3}$$

where iF_j = intake fraction of PM for industry j; iF_i = intake fraction of PM at state centroid i; and P_{ij} = fraction of sector j's emission in state i.

This approach assumes that for a given change of demand for any industry, the production level at facilities across the United States changes by the same proportion. This also assumes a linear relationship between emissions and production.

It should be noted that the tier 0 impact is calculated from the fiberglass emission factor and weighted intake fraction for fiberglass manufacturers' locations. On the other hand, the upstream impact (tier 1 and higher) is calculated from the industry-wide (i.e. 'mineral wool' industry) emission factor and the location-weighted intake fractions for all 'mineral wool' manufacturers. This assumes that while tier 0 output is specific to fiberglass, the upstream impacts are from both fiberglass and non-fiberglass manufacturers. This reflects an industry-technology assumption, which is commonly used in many input-output models. The assumption is that for all the commodities produced by an industry, the input mix is the same regardless of the commodities and is unique to the industry. In the case of insulation, this means that we assume, for the upper tier industry, that for all the commodities produced by the 'mineral wool industry', the input structure is the same regardless of the commodity produced (e.g. fiberglass and non-fiberglass products). This is a conservative assumption in that, even if the final product is only fiberglass, the upstream industries demand not only fiberglass insulation but also all the commodities produced by the mineral wool industry.

Thus, the first stage gives the upper and lower bounds as well as the central estimates of the emission-weighted intake fractions, which take into account the regional variability in source strength, population patterns and meteorological conditions. Because a primary source of uncertainty involves the stack height and the regression models, it would be useful to reduce the uncertainty by site-specific dispersion models as necessary. Therefore, the refined analysis concentrates on emission sites that explain a large portion of the total risk.

2.5 Refined analysis

To increase the accuracy of intake fractions for emissions from insulation manufacturers, we run a site-specific air dispersion model (ISCST3) to calibrate the CALPUFF-based ground-level source intake fractions to account for the actual stack height. To do this, we run ISCST3 for several important emission sites and calculate the ratio of intake fractions between ground-level emissions and actual stack height emissions. We then use the ratio as a scaling factor to calibrate the CALPUFF-based ground-level source intake fractions.

The first-level analysis is a screening stage where we evaluate the main sources of risk (e.g. > 50% for mortality). If the contribution from primary $PM_{2.5}$ is large, the intake fraction estimates should be refined by running site-specific air dispersion models because the near-source exposure is more

Table 1: Regression model parameters for power plant and mobile source intake fractions

	Primary $PM_{2.5}$	Nitrate	Sulfate
Power Plant	Population within 500km, Mixing height, 1/Stack height	Relative humidity, Log (sulfate iF), Wind speed	Population within 1000km, Relative humidity
Mobile	Population within 500km, Temperature, Relative humidity	Temperature, Log (sulfate iF), Relative humidity	Population within 1000km, Wind speed

important than for secondary pollutants like nitrates or sulfates. For the refining step, we select sources that accounted for at least 50% of the total upstream $PM_{2.5}$ emissions.

For both ISCST3 and regression-based ground-level source intake fractions at the actual plant locations, we use the meteorological data obtained for the weather stations that are closest to the source rather than the geographical centroids of the states. For the population estimates, we use CENSUS CD2000 to estimate the population within 500 km of the source, using census tract resolution [26].

One substantial limitation of our approach is that ISCST3 is recommended only for receptors within 50 km of the source, yet we apply it over a much larger region to capture the entire intake fraction. We tested a simplified long-range transport model (SLIM3) for receptors beyond 50 km, but the concordance between ISCST3 and SLIM3 was poor near the 50 km juncture. Therefore, we extended ISCST3 runs for the receptor regions beyond the 50 km point up to 500 km from the source. This assumes that the relative stack height effect is reasonably accurate even though the absolute concentrations at long range may not be accurate (and provides the rationale for basing our intake fraction estimates on CALPUFF, albeit with modifications).

To summarize, the steps included in deriving the best estimate of intake fractions for the selected sources are the following:

1. Apply the ground-level source regression model to estimate the upper bound intake fraction
2. Use ISC to calculate intake fractions for the facility location, using both the actual facility stack height and a ground-level source.
3. Multiply the upper bound intake fraction (Eq. 1) by the ratio of actual stack height and ground-level source intake fractions, as calculated by ISC (Eq. 2), to obtain the best estimate of intake fractions for the high-emitting facilities
4. Use the improved intake fractions from (Eq. 3) to re-calculate the emission-weighted intake fractions for the fiberglass/mineral wool industry.
5. Re-calculate health impacts using the revised best estimate (Eq. 4).

For the TRI chemicals, intake fractions previously published [27] are used to estimate exposure to the average person living in the United States. Although taking the entire United States as the receptor range does not address the regional variability in emissions and exposure, many of the hazardous air pollutants travel for long distances, and therefore, the approach is appropriate for screening level purposes.

2.6 Risk estimation

To derive the concentration-response relationships, we rely on a survey of the relevant epidemiological literature. For fine particles, we focus on premature mortality, since it contributes as much as 90% of the total social benefits from a monetary valuation perspective [15]. We also include morbidity in the form of asthma attacks and restricted activity days to provide a gradient of health outcomes. In addition, these health effect categories are consistent with our previous study, allowing us to compare the impacts associated with the end-use energy and the supply chain. The detailed discussion surrounding our determination of concentration-response relationships can be found in Nishioka et al. [1].

Cancer risks associated with toxic air pollutant emissions are calculated by applying the intake fractions of pollutants and the cancer potency factors, which can be found, for example, in the EPA's Integrated Risk Information System (IRIS) [28]. Under an assumption of no threshold of effects and a linear dose-response function, this gives a conservative upper-bound estimate, since the unknown true dose–response function may be a sigmoid shape.

Thus, cancer incidence associated with annual emission of chemical i is mathematically defined as the following:

$$Risk_i = iF\_tot_i \times CPF_i \times E_i \times 1/BW \tag{4}$$

where iF_tot_i = intake fraction of chemical i emitted to air or water and exposed to individuals (total US population) via inhalation, ingestion or dermal exposure; CPF_i = cancer potency factor of chemical i via inhalation, ingestion or dermal exposure $(mg/kg/day)^{-1}$; E_i = emission rate (mg/day); BW = average body weight in kg (assumed to be 62 kg) [25].

It should be noted that $Risk_i$ is a lifetime risk for the population given lifetime exposure, presumed to be approximately 70 years. To compare the cancer risks with the mortality and morbidity risks associated with the annual emissions of criteria pollutants, we divide the estimated cancer risks by 70.

2.7 Health valuation

Although significant uncertainty is associated with the monetization of health effects, the advantage of a valuation approach is to evaluate the relative magnitude of costs and benefits before and after including health effects. Since the direct economic cost-benefit calculation is often the major driver of demand-side management programs, it is useful to evaluate the impacts that would otherwise be discounted by excluding the upstream health impacts.

In cost-benefit analysis, the value of an adverse health effect is often defined as the amount a person would be willing to pay (WTP) to avoid the effect. In US EPA's review on health effect's valuation, WTP was a preferred estimate over a cost of illness (COI) approach, which usually underestimates the true value of avoiding the health effects. We use WTP or adjusted COI values in our cost-benefit analysis.

We determine a monetary value per statistical death as well as per case of asthma attacks and RAD from the US EPA benefit-cost analysis of the Clean Air Act [15]. For mortality, US EPA used the best estimate from each of 26 policy relevant value-of-life studies and fit a Weibull distribution, with a mean of \$4.8 million and standard deviation of \$3.24 million in 1990 dollars. The 26 studies consist of five contingent valuation studies, which directly elicit WTP from subjects, and 21 wage-risk studies, which derive WTP estimates based on the additional compensation that individuals demand in the labor market for taking riskier jobs. A central value for an asthma attack is \$32 (in 1990 dollars) based on a willingness-to-pay study that focused on avoidance of a bad asthma day. For RAD, a central estimate of

$60 (in 1990 dollars) is reasonable, given values of $38 for a minor restricted activity day (which is more mild than a restricted activity day) and $83 for a work-loss day (which is presumably more severe than a restricted activity day).

3 Conclusions

We have presented a methodology to incorporate regional variability in emissions and exposure into input-output LCA, using reduced-form information about the relationship between emissions and population exposure, along with standard input-output analysis and risk assessment methods. The location-weighted intake fractions can overcome the difficulty in incorporation of regional exposure in LCIA. In the second part of this paper, we apply the above methodology to evaluate the net public health impacts of increased residential insulation, given an input-output LCA framework. We also consider conclusions regarding the relative importance of upstream versus end-use emissions and implications for model development, as well as elements that contribute uncertainty to our analysis.

Acknowledgments. This research was supported by the North American Insulation Manufacturers Association.

References

[1] Nishioka Y, Levy JI, Norris GA, Wilson A, Hofstetter P, Spengler JD (2002): Integrating risk assessment and life cycle assessment: A case study of insulation. Risk Anal 22, 1003–1017

[2] Hohmeyer O, Brauer W (1995): Rational use of energy. In: Insulation of houses, energy efficient lighting, and frequency converters – Implementation externalities of fuel cycles. ExternE – Externalities of Energy Project. Germany: European Commission

[3] Bennett DH, McKone TE, Evans JS, Nazaroff WW, Margni MD, Jolliet O, Smith KR (2002): Defining intake fraction. Environ Sci Technol 36, 207A–211A

[4] Evans JS, Wolff SK, Phonboon K, Levy JI, Smith KR (2002): Exposure efficiency: An idea whose time has come? Chemosphere 49, 1075–1091

[5] Wolff S (2000): Evaluation of fine particle exposures, health risks, and control options. Doctoral thesis, Department of Environmental Health, Harvard School of Public Health, Boston, MA

[6] Levy JI, Wolff SK, Evans JS (2002): A regression-based approach for estimating primary and secondary particulate matter intake fractions. Risk Anal 22, 895–904

[7] Zhou Y, Levy JI, Hammitt JK, Evans JS (2003): Estimating population exposure to power plant emissions using CALPUFF – A case study in Beijing, China. Atmos Environ 37, 815–826

[8] Scire JS, Strimaitis DG, Yamartino RJ (1999): A user's guide for the CALPUFF dispersion model (version 5.0). Concord, MA: Earth Tech

[9] Krewski D, Burnett RT, Goldberg MS, Hoover K, Siemiatycki J, Jarrett M, Abrahamowicz M, White WH (2000): Particle epidemiology reanalysis project. Part II: Sensitivity analysis. Cambridge, MA: Health Effects Institute

[10] Whittemore AS, Korn EL (1980): Asthma and air pollution in the Los Angeles area. Am J Pub Health 70, 687–696

[11] Ostro BD, Rothschild S (1989): Air pollution and acute respiratory mobidity: an observational study of multiple pollutants. Environ Res 50 (2) 238–247

[12] U.S. Environmental Protection Agency (EPA): 1998 Toxics Release Inventory (TRI) Data Files <http://www.epa.gov/tri/tridata/tri98/data/index.htm>

[13] Abt Associates, ICF Consulting, E.H. Pechan Associates (2000): The particulate-related health benefits of reducing power plant emissions. Prepared for the Clean Air Task Force <http://www.cleartheair.org/fact/mortality/mortalityabt.pdf>

[14] Woodruff TJ, Caldwell J, Cogliano VJ, Axelrad DA (2000): Estimating cancer risk from outdoor concentrations of hazardous air pollutants in 1990. Environ Res 82, 194–206

[15] U.S. Environmental Protection Agency (1999): The benefits and costs of the Clean Air Act: 1990 to 2010 (EPA-410-R99-001). Washington, DC, EPA Office of Air and Radiation

[16] U.S. Department of Commerce, Bureau of Economic Analysis (2002): Benchmark Input-Output Accounts of the United States, 1998, data diskettes. Washington, DC

[17] U.S. Department of Commerce Economics and Statistics Administration, U.S. Census Bureau (1999): Mineral Wool Manufacturing 1997: Economic Census. Washington, DC

[18] Energy Information Administration, U.S. Department of Energy. Economic Profiles and Trends: Glass Industry Analysis Brief <http://www.eia.doe.gov/emeu/mecs/iab/glass/page1b.html>

[19] Energy Information Administration, U.S. Department of Energy. Residential Natural Gas Prices: What Consumers Should Know <http://www.eia.doe.gov/oil_gas/natural_gas/analysis_publications/residential_natural_gas_prices/Chapter1.html>

[20] Energy Information Administration, U.S. Department of Energy. Residential Heating Oil Prices: What Consumers Should Know <http://www.eia.doe.gov/pub/oil_gas/petroleum/analysis_publications/heating_brochure/heatbro.htm>

[21] Energy Information Administration, U.S. Department of Energy (1997): Electricity Prices in a Competitive Environment: Marginal Cost Pricing of Generation Services and Financial Status of Electric Utilities: A Preliminary Analysis Through 2015 <http://tonto.eia.doe.gov/FTPROOT/electricity/0614.pdf>

[22] Energy Information Administration, U.S. Department of Energy (2002): Petroleum Marketing Monthly 2002 <http://www.eia.doe.gov/pub/oil_gas/petroleum/data_publications/petroleum_marketing_monthly/current/pdf/pmmall.pdf>

[23] Energy Information Administration, U.S. Department of Energy (2002): Natural Gas Annual 2000 <http://www.eia.doe.gov/pub/oil_gas/natural_gas/data_publications/natural_gas_annual/current/pdf/nga00.pdf>

[24] Spengler JD, Wilson R (1996): Emissions, Dispersion, and Concentration of Particles. In: Particles in Our Air: Concentrations and Health Effects. Wilson R, Spengler J (eds), Harvard University Press, Cambridge, MA

[25] Center for International Earth Science Information Network (CIESIN), Columbia University; International Food Policy Research Institute (IFPRI); and World Resources Institute (WRI) (2000): Gridded Population of the World (GPW), Version 2. Palisades, NY: CIESIN, Columbia University <http://sedac.ciesin.org/plue/gpw>

[26] GeoLytics, Inc: Census CD 2000. East Brunswick, NJ

[27] Bennett DH, Margni MD, McKone TE, Jolliet O (2002): Intake fraction for multimedia pollutants: a tool for life cycle analysis and comparative risk assessment. Risk Anal 22, 905–918

[28] US Environmental Protection Agency (EPA): Integrated Risk Information System <http://www.epa.gov/iriswebp/iris/index.html>

Received: January 10th, 2002
Accepted: December 14th, 2004
(due to illness of the corresponding author)
OnlineFirst: December 14th, 2004